14.310x Flipped Classroom materials

—w3-1-links —-

rduranl

Course Guide

Week 1 Instructions	2
Week 2 Instructions	5
Week 3 Instructions	12
Week 4 Instructions	24
Week 6 Instructions	26
Week 7 Instructions	27
Week 8 Instructions	33
Week 9 Instructions	36
Week 10 Instructions	40

Week 1 Instructions

Some title

Checklist

Complete the Intro to R interactive course from the Swirl package ¹ (Requirement)
Watch the Getting started with Google Colab notebooks video tutorial (Requirement)
Create or set up a personal Google account (you must be able to use Drive and Colab). (Requirement)
Create your first Colab notebook (Session 1)
Complete Coding Lab 1. (Session 1)
Complete Coding Lab 2 (Session 2)

C.1.0

Your first Colab notebook

Instructions: Read and follow the steps below before proceeding with the activity. After reading the instructions, access the notebook link and complete the exercises in Colab. This is an individual task, but you will collaborate on the final question.

Notebook: Your first Colab notebook

¹Module 1 > Introduction to R in the online component of the course.

We will cover the essentials of working with Jupyter Notebooks on Google Colab—this resource will be an important tool throughout. Before you can begin working on the coding labs in Colab, make sure to:

- Create or use a personal Google account. While it is possible for you to download the Jupyter Notebooks we will work on, and manage them locally in your own machine, we strongly advise you to work on Colab since it will make it easier for your classmates and the instructor to interact with your work when needed. Colab has many features Google Drive already offers: comments, real-time colaboration in the same document or folder, etc.
- Save the shared notebooks and documents to your own drive. The notebooks you will have access to are read-only; in order to work on them you will have to copy them to your drive. It is recommended that you maintain a perweek structure in your folders as this will make it easier to follow instructions, especially when reading files or collaborating with others. To save the notebook to your Drive, go to the File menu: File > Save a copy in Drive.
- (When creating a new notebook) Change Colab Notebook's runtime type to R. By default, when you create a new notebook in Colab, the virtual machine Colab sets up for you is a Python installation. This means all the cells in the notebook will only recognize and run Python syntax or commands. To switch to an R language setup:
 - 1. Open the notebook menu and go to Runtime > Change runtime type.
 - Or click the toggle in the upper-right corner (as shown below) and select
 Change runtime type
 - 2. In the dropdown labeled Runtime type, select R.
 - 3. Click Save.



Fig. Changing the runtime type

You may now create your first Colab notebook

C.1.1

Coding Lab 1— Numeric data structures in R

Instructions: Work individually. Solve all exercises in the corresponding Colab notebook. Record your answers and/or code in your copy of the notebook.

Notebook: Coding Lab 1

Submit your work in the format required by the instructor.

C.1.2

Coding Lab 2 — Data manipulation with dplyr

Instructions: Work individually. Solve all exercises (sections 0 to 3) in the corresponding Colab notebook; record your answers and/or code in your own copy.

Notebook: Coding Lab 2

Optional **Section 4** allows work in pairs or teams of 3.

Upon completion, submit your work in the format required by the instructor.

Week 2 Instructions

Some title

Checklist

Complete the ADVANCED R interactive course from the Swirl package and watch the ggplot tutorial ² (Requirement)
Watch the $Import\ Data\ {\rm tutorial^3}({\rm Requirement})$
Read the note on importing aiwars and other datasets (Requirement)
$Complete\ Coding\ Lab\ 3\ ({\rm Session}\ 1)$
$Complete\ Guided\ Case\ 1 ({\rm Session}\ 2)$

Importing aiwars and other datasets

Depending on flipped classroom logistics of your group, your access to the sessions' assets (datasets, figures, scripts, etc.) will come in one of two forms:

- Through a direct URL for instance, the original aiwars.csv dataset lives directly in this URL:

 https://docs.google.com/spreadsheets/d/1NeZZWI2fT71M9QD8zjnz817T1B3XBM6lolqArSe9CwQ/export?format=csv
- Your instructor will provide them to you privately and they will either:
 - Share them via a URL similar to the one above.
 - Share the files through other means.

²Module 2 > R Course and R Tutorial: ggplot in the online component of the course.

³Module 3 > R Tutorials: Basic Functions in the online component of the course.

As they may want to slightly modify the original files for grading purposes, or have any other goal in mind.

If a dataset's URL is provided, you can read the data directly into R with the URL and the appropriate reading function; simply provide the URL as the path. For instance, aiwars is in .csv format:

```
URL_aiwars <- "https://docs.google.com/spreadsheets/d...."
aiwars <- read.csv(URL_aiwars)</pre>
```

And similarly for other formats. Suppose we had a single Excel sheet:

```
install.packages("readxl")
library(readxl)

URL_aiwars_xl <- "https://...some-URL"
aiwars <- read_excel(URL_aiwars_xl)</pre>
```

If the file is shared in any other way, we will first need to upload it to the virtual machine's disk in Colab and read it from there, providing the path to it — as you would do if you were reading data to R in your own computer. To upload a file in Colab, click the folder icon in the leftmost menu bar, as shown in the screenshot. Then click the upload icon (circled in red); as you can see, we already uploaded the file.



Once uploaded the file can be read as a if in your machine:

```
aiwars <- read.csv("aiwars.csv")
```

Important: Colab runtime limitations

While your Colab notebook — including all code cells, text, and outputs — will remain saved, the underlying *runtime* (i.e., the virtual machine that executes your code) is temporary. After a period of inactivity or when a time limit is reached, the runtime will automatically disconnect.

When this happens:

- All variables and objects stored in memory (e.g., your R data frames, models, vectors) will be lost.
- Any files you uploaded manually will be erased.

When reconnecting, a fresh virtual machine will be started, and you'll have to re-run your code, and re-upload any needed files. Disconnects may happen occasionally as you work in off-notebook tasks; re-reading or re-uploading files should not take over 30 seconds.

Coding exercises in case studies

Throughout the course, the case studies you will work on contain a mix of conceptual and coding questions. To simplify your workflow, all the questions where you're required to write code are specially labeled. They appear in this format:

Question 5. \square > [2.3] calculate the probability of event A...

The small icon signals that the question requires coding. The number inside the brackets (2.3 in this example) is a numbering within the Session's dedicated Colab notebook, which will often be different from the overall question number for the activity.

Further, if you click on the orange icon, it will take you directly to the question's cell within the Notebook by opening a new browser tab – remember you must work on your own copy of the notebook. These links are simply provided as a convenience to help you locate and visualize the relevant task quickly.

Apart from being the place where you are expected to code your answers, the corresponding cell usually includes a placeholder for your code, often accompanied by additional hints, extended context, or partially completed code to help you get started. When working on a case study, keep both this PDF and Colab notebook open and use these references to move smoothly between the written materials and your code.

C.2.3

Coding Lab 1 — Web Scraping in R: step by step guide

Instructions: Work individually. Solve all exercises in the corresponding Colab notebook. Record your answers and/or code in your copy of the notebook, or in the format required by the instructor.

Notebook: Coding Lab 1

Case study G.2.1

Random variables in the wild: *Reddit* posts and empirical distributions

Instructions: Work in pairs or groups of three. Answer the questions

Notebook: Case Study 1

□ Dataset: aiwars.csv

One of you must share editor access to their notebook with the rest.

Scenario: We will cover this week's lecture contents using a real-world dataset from Reddit. You will put your data manipulation (with dplyr and base R) skills to practice

Context: The AIwars dataset consists of a collection of posts scraped from the r/AIwars subreddit, a forum where users debate the societal implications of AI. These range from predictions about AI-driven job loss and technological conflict to satire, trolling, and speculation. The dataset captures a rich period of discussion and polarization. Each observation corresponds to a single post, with information about its author, contents and engagement.

Key Variables:

- post_index Unique identifier for each post (starts at 1 and consecutively numerates all posts).
- author Reddit username of the post author (may be [deleted]).
- \bullet post_date an R Date
- fulltext Full text of the Reddit post in format TITLE: [some post title] TEXT: [some post text]
- post_length the net number of characters in fulltext (excluding the TITLE and TEXT headers).
- post_upvotes Number of upvotes (user endorsements or *likes*) the post received.
- comments_number Total comments the post received (includes replies to other comments).

Part 1. Basic dataset facts

- 1.1 [1.1] Install and load the tidyverse packages. Create aiwars_URL, a character with the download URL for aiwars.csv. Then read in the dataset as aiwars, a data frame. Use glimpse() to answer:
 - (a) How many posts are we working with?
 - (b) How many variables does the dataset have?
 - (c) How many are true character types?
 - (d) How many are numeric?
 - (e) Which characters are better described as factors? Why?

- 1.2 [1.1.1] For the entire case study, will use only the **Key Variables** described above. While **select()**ing columns from the current data frame is possible, a memory-efficient alternative is to read in only those columns we need. Use the **col_select** argument in **read_csv()** to create **aiwars_short**, a data frame containing only the columns described as **Key Variables**.
- 1.3 [1.1.2] Use select() to create aiwars_short2, a dataframe with only the key variables.
- 1.4 Moving forward we will work with aiwars_short only. You may delete rm(aiwars, aiwars_short2).
- 1.5 Use summary() or other summarizing methods to answer the following questions:
 - (a) What is the time span of the posts?
 - (b) On average, how long (in words) is a post on this subreddit?
 - (c) How many posts don't have any replies?
 - (d) What is the largest number of upvotes in a post?
 - (e) Which author has posted the most? (Consider as.factor()).
 - (f) How many distinct users have posted in this subreddit? (Consider unique()).

Part 2. Counting posts

- 2.1 [2.1] Create the following variables in aiwars_short:
 - (a) popular, takes value 1 when the post has 29 or more upvotes. Takes value 0 when the post has less than 29 likes.
 - (b) text_classification, which takes value mostly title if it is less than 70 characters long, short if it has 70 or more but less than 110 characters, common if it has 110 or more but less than 900 characters, and long if the post has over 900 characters.
- 2.2 How many common posts are there?
- 2.3 If we draw a post at random, it will be a popular one with what probability?
- 2.4 If we instead sample 10 posts at random with replacement, what is the probability 3 of them are popular?
- 2.5 \square >_ [2.2] Suppose random variable X; $\Omega_X = \{0, 1, 2, ..., N\}$ represents the number of popular posts in N = 10 draws with replacement from aiwars_short. For the following probability statements describing various events, first write them down as a probability and then use R to compute them.
 - (a) What is the probability of getting at most 4 popular posts?
 - (b) What is the probability of getting at least one but at most 3?
 - (c) What is the probability of getting a number of popular posts that is not 0 or 4?
- 2.6 Similarly, we can treat the texts' classification as random variable Y. Is it continuous or discrete? What is Ω_Y ?

 Ω_Y and two columns: y, the value taken by Y and p its mass or density.

- 2.8 What is the probability a post is not mostly title?
- 2.9 What is the probability a post is either common or long?

Are popular posts different?

2.10 What is the probability a post is popular **AND** long?

As we learned from the lecture, if two events are **not independent**, the additional information one of them provides should *update* the probability of the other. We will examine this fact by calculating the probability of a post being long **GIVEN** that we know it is popular:

$$P(Y = long \mid popular = 1)$$

As a reminder:

$$P(long \mid popular = 1) = \frac{P(long \cap popular = 1)}{P(popular = 1)}$$

- 2.11 Use your answers to questions 2.3 and 2.10 to compute the probability a post is long GIVEN it is popular. How does this probability compare to the unconditional probability P(Y = long)?
- 2.12 We now know that the event (Y = long) has two mutually exclusive and exhaustive partitions: (popular = 1) and (popular = 0). Following the lecture, Show that the Law of Total Probability verifies for this event.
- 2.13 What is $P(popular = 1 \mid long)$? Is your answer the same as in 2.11? Should it be? Why?
- 2.14 \bigcirc **\(\sum_{1} \)** [2.4] Create **joint_pmf**, a data frame similar to the one you created for 2.7; in this case, it should display the probability for all possible values in $Y \cap Popular$. This is the ordered pair $\Omega_Y \times \Omega_{Popular} = (long, 1), (long, 0), ..., (mostly title, 1), (mostly title)$
- 2.15 \bigcirc \(\sum_{\text{[2.4.1]}}\) Use joint_pmf, p (or $f_{popular}$) and f_Y to compute the following in R:
 - (a) $P(Y \mid Popular = 1)$, a vector of length 4.
 - (b) $P(Popular \mid Y = common)$. What is its length? .

Week 3 Instructions

Some title

Checklist

□ Complete Guided Case Study 2 (Sessions 1 & 2)
 □ We will continue to work with aiwars
 □ Get the aiwars_embeddings dataset here
 □ Complete Open Case Study 1 (Session 2)

Case study G.3.2

Analyzing text similarity: language semantics and random variables

Instructions: Work on your own for Session 1, and in pairs or groups of 3 for Session 2.

Notebook: Case Study 2

Dataset: aiwars_embeddings.csv

Part 1 Part 2 Part 3

Dataset: speech_anchors.csv

The aiwars_embeddings dataset (split into three parts for file-sharing purposes) contains 1024 variables associated with each post's fulltext. You will learn what these embedding variables V1, V2, ..., V1024 represent below, but keep in mind post_index in both datasets uniquely links each post in aiwars to its embedding in aiwars_embeddings. Dataset speech_anchors is a 2-row data frame with the same structure.

Part 0. Required data and packages

- 0.1 [0.1] Load/install the tidyverse and the geometry packages.
- 0.2 [0.1] Read in aiwars, the same dataset as last week. Also, read in speech_anchors.csv as anchors. This should be a data frame with two rows and 1025 columns.
- 0.3 [0.1] Read in parts 1,2 and 3 of aiwars_embeddings as part1, part2,part3 respectively. Then use rbind() to vertically merge the parts into aiwars_embeddings. Optionally, use arrange() to sort the dataset in post_index- ascending order.

Scenario:

Natural Language Processing (NLP) focuses on enabling machines to understand and work with human language. One of the key advances in NLP has been the development of methods that represent text — such as words, sentences, or entire posts — as vectors. These vector representations, often referred to as *embeddings*, capture aspects of a text's semantic content: its meaning, tone, and topical focus.

To illustrate the idea, suppose we have the following texts:

- Text A: "I love how these new AI tools can generate art!"
- Text B: "AI-generated images are cool, but I'm worried about copyright."
- Text C: "I painted this myself no software involved."

We embed these texts in 2-dimensional vectors from the origin, plotted below:

$$\vec{a} = \begin{pmatrix} x_a \\ y_a \end{pmatrix} = \begin{pmatrix} 0.8 \\ 1.6 \end{pmatrix}$$

$$\blacksquare \vec{b} = \begin{pmatrix} x_b \\ y_b \end{pmatrix} = \begin{pmatrix} 1.7 \\ 2 \end{pmatrix}$$

$$\blacksquare \vec{c} = \begin{pmatrix} -1 \\ 0.3 \end{pmatrix}$$

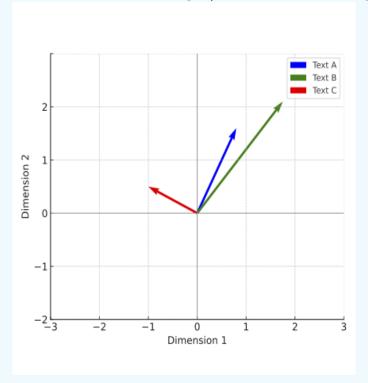


Figure 1: 2D text embeddings (vector from the origin)

Despite their differences in tone, \vec{a} and \vec{b} in Figure 1 are close to each other because the texts they represent use AI-related language, whereas \vec{c} is far removed given the lexical differences. In part 2, we will explain what "close to each other" means for vectors, with two common semantic similarity measures: **direction** (i.e., the *angle* they form) and **distance** between them.

Part 1. Coding vector operations

You will start by programming functions necessary for this analysis, such as the magnitude of a vector, the distance between two vectors, their dot product, etc.

Distance between two vectors

The distance from \vec{a} to \vec{b} in Figure 1 is defined as:

$$||\vec{a}, \vec{b}|| = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}$$

This is the sum of their x and y-coordinates' differences squared (in any order). Finally, we take the square root of that sum. Substituting the values in the scenario description:

$$\dots = \sqrt{(0.8 - 1.7)^2 + (1.6 - 2)^2}$$

$$\dots = \sqrt{0.81 + 0.16} = 0.985$$

- 1.1 Save $\vec{a}, \vec{b}, \vec{c}$ as numeric vectors **a**, **b** and **c** respectively. Compute the distances for each pair of vectors and save them accordingly: **dist_ab**, **dist_ac**, **dist_bc**. Hint: you can apply operations on all the coordinates at once: (a-b).
 - (a) Make sure your result for dist_ab is the same as above.

In general, to get the distance between any two n-dimensional vectors

$$\vec{V} = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{pmatrix}, \vec{U} = \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix}$$

we generalize the process with all their coordinates and take the square root:

$$||\vec{V}, \vec{U}|| = \sqrt{(v_1 - u_1)^2 + (v_2 - u_2)^2 + \dots + (v_{n-1} - u_{n-1})^2 + (v_n - u_n)^2}$$

$$\cdots = \sqrt{\sum_{i=1}^{n} (v_i - u_i)^2}$$

- 1.2 \triangleright [1.2] aiwars_embeddings contains a 1024-dimensional vector per post. Program a distance function dist_function(V, U) that takes any two equallength, numerical vectors. It returns the distance between them. If you didn't in the previous exercise, make sure to use vectorized operations (e.g., sum(), squaring all elements at once as $(a-b)^2$) to generalize the computation.
 - (a) Verify your function is correct and reproduce the results in 1.1

Distance from one, to multiple vectors

Working with individual, separate objects such as $dist_ab$, $dist_ac$, and so on can be difficult and tedious. In R, we will often want all the distances with respect to \vec{a} in a single "distances" vector or variable:

$$D_a = \begin{pmatrix} || \vec{a}, \vec{a} || \\ || \vec{a}, \vec{b} || \\ || \vec{a}, \vec{c} || \end{pmatrix}$$

We will now pass dist_function() trhough all the example vectors at a time to obtain D_a — the steps should be familiar from the previous Coding Lab.

- 1.3 \square >_ [1.2.1] Create vector D_a with a for loop by following the steps below:
 - Declare **D_a**, an empty vector.
 - Use rbind to create examples_matrix, a matrix with 3 rows and 2 columns.
 One row for each example vector a,b,c and one column for each of their x, y-coordinates.

- Declare a for(...)... loop with as many iterations as rows in examples_matrix.
- Inside the *for* loop, code the following:
 - Subset examples_matrix to obtain vector v.
 - Obtain the distance between a and v with dist_function.
 - Use append to recursively add a distance on each iteration to vector D_a.
- 1.4 Verify your answers with those of 1.2. What should be the result for $||\vec{a}, \vec{v}||$ when $\vec{v} = \vec{a}$? Why?

Finally, we can wrap the code we created for 1.3 in a function that directly returns D_a when given a vector and a matrix.

- 1.5 \square \(\sum_{\text{[1.2.2]}}\) Create a function get_distances(u, M) which takes a vector u of length n and a matrix M with an arbitrary number of rows k, and n columns. The function should return D_u , a vector of length k where each element is the distance between vector and a row of matrix.
- 1.6 Use get_distances(_,_) to reproduce 1.3. Verify it is the same vector.

The norm of a vector

The norm $||\vec{V}||$ (also called the *magnitude* or *length*) of a vector indicates how long the arrow is from the origin to the point it reaches. Since all embeddings are vectors at the origin (all their starting coordinates are 0), we can calculate this as the distance between a vector \vec{V} and the n-dimensional zero: $||\vec{V}, \vec{0}||$.

$$||\vec{V}, \vec{0}|| = ||\vec{V}|| = \sqrt{(v_1 - 0)^2 + \dots + (v_n - 0)^2}$$

$$\dots = \sqrt{\sum_{i=1}^{n} v_i^2}$$

- 1.7 [1.3] Create normO_function, a function that takes V, a numerical vector of length n as an input, and returns its norm from the origin. Hint: you can recycle dist_function inside return() with the appropriate U.
- 1.8 \bigcirc [1.3.1] Compute $||\vec{a}||, ||\vec{b}||$ and $||\vec{c}||$. Save them to a_norm, b_norm, c_norm respectively.
- 1.9 Similar to 1.3 and 1.5, create a function get_norms0(M) taking a matrix of n rows/vectors, all with the same number of dimensions/columns m, and returns a vector N_0 of length n with a norm from the origin for each row/vector in M. Input it the examples_matrix and verify your results in 1.8.

The dot product of two vectors

The dot or scalar product of two vectors $\vec{U} \cdot \vec{V}$ is defined as the sum of the product of each pair of their coordinates:

$$\vec{U} \cdot \vec{V} = u_1 * v_1 + u_2 * v_2 + \dots + u_n * v_n$$

$$=\sum_{i=1}^{n}u_{i}v_{i}$$

You can use R's native vectorized multiplication: sum(u*v).

- 1.10 [1.4] Create a function dot_product(u,v) that takes two numeric vectors of the same length as input and returns their dot or scalar product.
- 1.11 \square \triangleright [1.4.1] As in previous exercises, we're interested in computing a vector \mathbb{D}_a of dot products. Use a *for*-loop and wrap it in a function $\mathtt{get_dot_products}(\mathbf{v}, \mathbf{M})$ taking a vector \mathbf{v} of length n and a matrix \mathbf{M} of as many rows as vectors and n columns and returns a dot product $\vec{V} \cdot \vec{m}$ for each row.

Part 2. Processing AIwars posts' text embeddings

We prepared the aiwars_embeddings dataset for you by using one of OpenAI's text embedding products¹. For each post's fulltext in aiwars, there is a vector representation of length n = 1024 in aiwars_embeddings:

Variables

- post_index: a consecutive index in the same order as aiwars. A given post and its embedding share the same post index.
- V1, V2, ..., V1024: the coordinates $v_1, v_2, ..., v_{1024}$ of each vector embedding \vec{V} .

You will now apply the functions you previously programmed to measure the semantic similarity of real-world embeddings.

Semantic similarity measures: Luddites vs Synthists

To illustrate semantic similarity measures, we will take the embeddings from four select posts from the AIwars subreddit, each with distinct tones and topics:

- 2.1 [2.1] Filter aiwars for posts with the following post_index values: 456, 584, 2397, 2526. Select the fulltext and post index columns only. Assign the resulting dataframe to tones.
- 2.2 Skim the title and body of each of the posts in tones.
- 2.3 Create a character vector post_labels <- c("luddites", "review", "critique", "synthists"). Sort tones in ascending post_index order and add the vector as a new variable label.
- 2.4 \square >_ [2.2] Retrieve the embeddings for tones in a 4×1024 matrix and save it as tones_embeddings:
 - (a) Filter aiwars_embeddings for the relevant post_index.
 - (b) Either drop post_index or tidy-select all variables starts_with() "V".
 - Remember to keep track of the embeddings. We suggest you previously arrange by ascending post index.
 - (c) Coerce the resulting data frame into a matrix with as.matrix()

.

Distance-based semantic similarity

As exposed in the introduction, if two texts share style, vocabulary or topics, their embeddings will tend to be closer, and on the contrary, distinct semantics will produce embeddings that are farther apart.

Table 1: Pairwise distances between example embeddings (not the real values)

	luddites	review	critique	synthists
luddites	0.0000000	72.384921	18.532947	91.004327
review	72.384921	0.0000000	56.110239	8.231476
critique	18.532947	56.110239	0.0000000	44.873291
synthists	91.004327	8.231476	44.873291	0.0000000

Code a 2-D distance matrix like the one displayed above with the embeddings in tones. Hints:

- This is a matrix with rownames and colnames
- Use rbind to save each iteration on tones.
- Note: the matrix you get should be symmetrical. The distance between *critique* and *luddites* should be the same in (row 1 column 3) and (row 3 column 1).
- 2.6 Before you reflect on the results, consider what the bounds could be:
 - (a) If the embeddings could be of any magnitude, what would be the maximum distance between embeddings?
 - (b) Compute the norm about the origin for the embeddings in tones. What can you notice?
 - (c) Compute the norm for all of aiwars_embeddings by getting a matrix for all the embeddings as in 2.4.
 - (d) Based on this observation, what is the longest possible distance between two of these embeddings?
- 2.7 Which embedding pair is the furthest apart?
- 2.8 Which individual embedding seems to be further away from the rest?
- 2.9 Which two embeddings are the closest?

Direction-based measures: Cosine Similarity

An alternative approach is to compare the vectors' direction only, through the angle θ formed by two vectors \vec{a}, \vec{b} . The cosine of said angle θ is defined as:

$$cos(\theta) = \frac{\vec{a} \cdot \vec{b}}{\mid\mid \vec{a} \mid\mid \mid\mid \vec{b} \mid\mid}$$

- $\cos(\theta) = 1$ means the angle is $\theta = 0^{\circ}$, indicating identical direction. These texts will be very close in meaning and topics.
- $\cos(\theta) = 0$, the angle is $\theta = 90^{\circ}$, indicating the posts are orthogonal, and for the most part, semantically unrelated: different topics and intent.
- $\cos(\theta) = -1$, with angle $\theta = 180^{\circ}$, vectors point in opposite directions.

In our setup, cosine similarities in [0.5, 0.7] usually indicate a non-trivial topical relation; values ≥ 0.8 often reflect very close texts (near-paraphrases). Scores in [-0.3, 0.3] are not indicative of a strong semantic link. ≤ -0.3 cosines can occur but are uncommon and shouldn't be interpreted as "opposite views" on their own—you should inspect the post instead.

- 2.10 \bigcirc [2.4] Write a function batch_cossim(u,M) taking a vector of length n and a matrix with k row-vectors and n columns, returning the cosine of the angle θ between u and each row-vector. Keep in mind what you learned in 2.6b and consider that class of vectors only.
- 2.11 [2.5] Similar to 2.5, create a cosine similarity 2-D matrix for the tones embeddings. The diagonal elements must all be equal to 1.

AI-awareness and Simplicity measured in the aiwars posts

For the next case study, we shift our attention to general qualities within the posts. We're interested in vector directions capturing meaningful, human–interpretable features. For the AIwars subreddit, a predominant topical direction is that of AI awareness. It is also possible to track a stylistic direction that contrasts short, slogan-like, low-context statements with longer, hedged, evidence-seeking discussion; we refer to this as anti-nuance or simplicity.

The embeddings corresponding to said features are contained in speech_anchors.

- 3.1 [3.1] Create vectors ai_awareness and simplicity, the cosine similarities between the aiwars_embeddings dataset and each of the speech_anchors previously discussed. Add them as variables of aiwars for your next case study—remember to previously arrange both datasets by ascending post_index.
- 3.2 save the new dataset as aiwars_updated to use during this week's next session.

Case study O. 3. 1

Instructions: Work in pairs or groups of three; solve the following exercises collaboratively, and put together the deliverable specified in Part 2.

Notebook: Open Case Study 1

Dataset: aiwars_updated.csv

One of you must share the case study's notebook (parts 1 and 2) and a blank slides or text document (part 3) with the rest.

¹The coordinates for each embedding are outputs of a more complicated embedding model involving several neural networks architectures and outside the scope of this course. For this week's case studies will limit ourselves to work with the embedding themselves.

Part 1. Discrete and continuous methods

0.1 [0.1] Read in aiwars_updated; load/install the tidyverse packages.

Consider two continuous variables related to the semantics of text posted by redditors in r/Aiwars:

- **AI-awareness**: A, the extent to which a post's vocabulary and syntax depict artificial intelligence topics.
- **Simplicity**: S, a post's reliance on short, declarative phrasing and minimal argumentative or conceptual complexity.
- 1.1 Based on your previous knowledge, what are the sample spaces Ω_A , Ω_S ?
- 1.2 Provide a short explanation as to why these can't be discrete random variables.
- 1.3 \square \triangleright [1.1] Use ggplot2 to create A histogram plot for both A and S on the same x-axis.
 - (a) Declare a ggplot() on your data frame.
 - (b) Add a geom_histogram() layer with ai_aware as your x-aes(). Outside aes(), set the fill parameter to "blue", the color to "black", and the transparency (alpha) to 0.5.
 - (c) In the same plot, add another histogram layer analogously for simplicity but fill it with "red".
- 1.4 Examine the plot:
 - What is the *y*-value?
 - At what range of x-values does ai_aware have more observations?
 - If we summed all y-values of the bins in the simplicity histogram, what should be the result?
 - Can we tell exactly what $f_A(0.5)$ or $f_S(0.75)$ are? Why or why not?
- 1.5 More generally, which histogram seems more concentrated around a given range of values?
- 1.6 Are these histograms valid distributions?
- 1.7 We want the y-value to reflect a probability. Edit the aes() function in your histograms to include the following y-aesthetic: y = after_stat(count/n). Compute and save n separately.
- 1.8 Similar to 1.4, what should be the sum of all the bins' y-values of any histogram?
- 1.9 Very roughly (no computation needed), what is x such that $F_A(x) \geq 0.5$?
- 1.10 Again roughly, what do you think $F_S(0.1)$ approximates to?
- 1.11 Histograms are discrete representations of a RVs. Change the binwidth of just the red histogram to 0.01. What can you observe? Did the distribution's relative shape change? Why?
- 1.12 Examine the new plot. What is the default bin width for the blue histogram then?

Recall the Summarizing and Describing Data lecture. We can get a **continuous** representation of our RV's distribution through kernel density estimation. Base R has a readily available function for this: **density()** — feel free to test it in your own time.

We will use ggplot2's version: geom_density() to plot the estimated pdfs $\widehat{f_A(\cdot)}$ and $\widehat{f_S(\cdot)}$ for all the x-values in the domain of our data.

- 1.13 [1.1] Copy and paste your last histogram plot. Delete the y argument in aes() in both histograms. Substitute geom_histogram with geom_density in both layers.
- 1.14 Exclusively in terms of shape and position relative to each other, how do these distribution representations compare to those in 1.3?
- 1.15 Now examine the y-axis. How does it compare to your plot in 1.3?
- 1.16 Roughly, what is $max f_S(x)$? What is the minimum for both?
- 1.17 Are these valid distributions? To help you answer this question, consider random variable $M \sim U[0, \frac{1}{4}]$, a uniform distribution from 0 to 0.25; write down its pdf $f_M(m)$.
- 1.18 Roughly from the plot, what is $P(0.125 \le S \le 0.25)$?
- 1.19 Go back to your second plot in 1.3 and compute $P(0.125 \le S \le 0.25)$.

Another way to compute the probability of an event for a continuous RV is through its CDF. Recall from the lecture that

$$P(a \le X \le b) = \int_{a}^{b} f_X(x)dx = F_X(b) - F_X(a)$$

Base R allows us to create a function for the empirical CDF of continuous variables with ecdf(). This function also has its ggplot2 analog in stat_ecdf(), which you can use just as any other geom.

- 1.20 [1.3] Use ecdf() to create functions F_A and F_S, the empirical CDFs of A and S respectively. Make sure you have the correct object by quickly plotting the CDFs: plot(F_A), plot(F_S). Then answer the following questions:
 - (a) $F_S(0.25)$?
 - (b) $F_A(0.25)$?
 - (c) What is $s \in \Omega_S$ such that $P(S \le s) = 0.8$?
 - (d) What is $a \in \Omega_A$ such that $1 P(A \le a) = 0.1$?
 - (e) Compute the extremes event probability for A: $P(S \le 0.36 \cup S \ge 0.6)$
 - (f) Make a 95% inner interval for S. Find any $a,b\in\Omega_S$ such that $P(a\leq S\leq b)=0.95$
- 1.21 \bigcirc [1.4] Use stat_ecdf() in ggplot2 to jointly plot the CDFs for A and S. Make sure to color them blue and red, respectively.
- 1.22 Can you conclude there's first-order stochastic dominance of one of the random variables to the other?
- 1.23 In the lecture, height was the construct measured for women in both Bihar and the US. Are S and A measuring the same thing in the posts?
- 1.24 What, if any, could the implications of FOSD be in this case?

Part 2. Non-independence

- 2.1 Within the r/AIwars subreddit, conditional on learning posts tend to be long and argumentative, would their probability of being AI-related change?
- 2.2 \square >_ [2.1] Let's begin by examining $f_{A,S}(a,s)$. Use ggplot2's function geom_bin_2d() to plot a 2D-histogram with ai_aware in the x-axis and simplicity in the y-axis.
- 2.3 What does color represent in this plot? Note that the "minimal" unit colored is a rectangle tile.
- 2.4 Are the x and y-bandwitdths the same? What are they, approximately?
- 2.5 Similar to 1.8, modify the color to show a probability with after_stat(). This time change the fill aesthetic.
- 2.6 Generally describe the joint composition of the subreddit's posts in terms of their AI-awareness and their simplicity.
- 2.7 Do short, declarative post tend to discuss AI extensively?
- 2.8 Do relatively long and argumentative posts necessarily discuss AI deeply and technically?
- 2.9 What is the semantic region $\Omega_S \times \Omega_A$ most posts fall in?
- 2.10 **True** or **False**: if A and S were independent, we would have a perfectly squared 1×1 grid and all tiles would be of the same color, because $f_{A,S}(a,s) = f_A(a) \cdot f_B(b)$

Numerically, we can represent the joint pdf $f_{A,S}(a,s)$ of these two cotinuous RVs as plotted in 2.2 is a matrix with rows and columns corresponding to each x (ai_aware) and y-bin (simplicity), with a large number of bins. The next question's code will create such a matrix, f_AS for you. It should be 30×30 .

- 2.11 \square \triangleright [2.2] Run the pre-scripted code to get f_AB , the joint PDF $f_{A,S}(a,s)$. Then compute the marginals $h_A(a)$ and $h_S(s)$ and save them as h_A and h_S , respectively. Keep in mind these should be vectors of length 30.
- 2.12 Make quick base R plots of each marginal with $plot(y = h_A, x = as.factor(names(h_A)))$ and similarly for h_S in a separate plot. Do they look familiar? Why?
- 2.13 Use f AS, h A or h S and their bin names to calculate the following:
 - (a) $P(S \le 0.36 \cap A \ge 0.628)$
 - (b) $P(0.15 \le S \le 0.36 \cap 0.628 \le A \le 0.859)$
 - (c) $P(S = 0.188 \cap A \le 0.923)$
 - (d) P(A > 0.628)
 - (e) $P(A \ge 0.628 \cap 0.27 \le S \le 0.3)$
 - (f) $P(A \ge 0.628 \mid 0.27 \le S \le 0.3)$
 - (g) $P(A \ge 0.628 \mid 0.27 \le S \le 0.419)$
 - (h) $P(A \mid 0.27 \le S \le 0.3)$. Save as A_cond and plot this
 - (i) $P(S \mid A \in (0.795, 0.827])$. Save as S_cond and plot.
- 2.14 Based on your answers to 2.13f to 2.13i, are A and S independent?
- 2.15 Particularly on 2.13h and 2.13i, if A, S were independent, what should these plots look like? What differences can you notice?
- 2.16 Optionally, plot $f_{S|A'}(s|a=A')$ or $f_{A|S'}(a|s=S')$ alongside the curve they should

approximate under independence.

2.17 \square >_ [2.3] Finally, directly verify the claim in 2.10. Use h_A and h_S as well as a double (nested) loop to produce $g(a,s) = h_A(a) * h_S(s)$ for the same 30×30 grid. Then use heatmap() with the same arguments used in the previous code snippet to examine the joint density. Does this look like a homogeneous distribution? If not, why? If it does, at what regions of $\Omega_A \times \Omega_S$ do we have missing values, if any?

Part 3. Your own joint distributions

Your team will freely analyze the relationship between either AI-awareness or Simplicity and one other feature in the aiwars dataset.

Create a short deliverable following these instructions:

- Choose either ai_aware or simplicity and one other key variable.
- Your instructor will
 - Approve or change your choice based on their goals and what other students are working on.
 - Inform you of the format required for the deliverable. Usually a 5-slide eck or a show text document.
- Once your choice is approved:
- Once your choice is approved:
 - 1. Construct the joint distribution of the two variables (Depending on your choice of discrete or continuous, use a geom_bin_2d, a boxplot, or any of the plots reviewed in the lecture).
 - 2. Obtain and interpret the marginal distributions of each variable.
 - 3. Compute the conditional distributions (e.g. $f_{A|X}(a)$ or $f_{S|X}(s)$) for what you consider are relevant ranges of values. Evaluate how independent the analysis variables are.
 - 4. Include at least one visualization that helps highlight the relationship (histograms, heatmap, density plot, etc.).
 - 5. Provide 1–2 slides (or short paragraphs) summarizing the implications of the independence (or lack thereof) between variables plain language: What does the relationship tell us about Redditor behavior?
- Submit as required. Your instructor will let you know if your team will briefly expose your deliverable to the class.

Week 4 Instructions

Some title

Checklist

- ☐ Complete Coding Lab 4 (Sessions 1 & 2).
- ☐ (Optional) Explore the **Review Notes** and further **Readings** available.

Coding lab L.4.4

Understanding Probability and Statistics in R: A Step-by-Step Guide

Instructions: Work individually. Answer all questions in sections 1-6. Sections 7 and 8 are optional; follow your instructor's directions.

Notebook: Coding Lab 4

Record your answers in your copy of the notebook, or in the format required by your instructor.

Additional resources

- Drive: Review Notes

- Drive: Readings

Week 6 Instructions

Some title

Week 7 Instructions

Some title

Checklist

Set aside this Wikipedia article on testing two-proportions hypotheses, in case you need it during Session 2 $_{\rm (Requirement)}$
Skim this Wikipedia article discussing the Local Average Treatment effect (LATE) , in advance of Session 2. $_{\rm (Requirement)}$
Complete Guided Case Study 3 invidually (Session 1)
☐ Retrieve the students dataset here
Complete Open Case Study 2 in pairs or teams of 3. (Session 2)
☐ You will continue to use students

Case study G.7.3

Evaluating AI-assisted learning on student outcomes

Instructions: Work on your own; read the scenario and answer the questions. Type your answers in the format required by the instructor.

To work on the students dataset you may use either a Colab notebook or your own installation of R.

Dataset: students.csv

Your code will not be evaluated, but keep your R script or notebook tidy, as you may need to review some of your answers during Session 2.

Scenario:

You are the Government of *Novaria*'s new Minister of Education. The Prime Minister has tasked you with evaluating a primary education policy recommendation: the rollout of AI-assisted learning for mathematics curricula in grades 5-8.

The proposed program, *Project Mentor*, involves deploying a large language model (similar to ChatGPT) named *AlgebrAI* specifically trained and fine-tuned for elementary math tutoring. AlgebrAI's interface is tailored to deliver interactive, one-on-one tutoring sessions to students. The AI mentor adapts to each student's skill level and provides problem-solving guidance, hints, and feedback designed to help the students master their grade's math curriculum.

Each participating school receives a number of tablets with AlgebrAI pre-installed, configured for offline-first use and automatically synced with central servers when internet is available. Students selected for treatment attend 20-minute tutoring sessions per day under the supervision of a facilitator.

The Prime Minister believes Project Mentor can boost test scores nationwide, but political opponents have raised concerns over cost and long-term efficacy. You are now in charge of evaluating the impact of the program in grades. Your team provides you with:

- 1. A 6th-grade math test designed to perfectly measure domain of the curriculum in a scale from 0 to 100.
- 2. A list of 1,000 students enrolled in 6th grade across Novaria, picked at random part of the students dataset. This list contains only the following variables:
 - unit: a consecutive number assigned to the student.
 - W_school: Indicates whether the student's school is managed by the government $(W_{school} = 1)$ or if it is privately managed $(W_{school} = 0)$

You have authority to apply the exam to any 6th grader in Novarnia, and you can implement the program (tablet usage and monitor time) in all government-managed schools, but to include any students attending a private school to the program you must first obtain authorization from their school board.

Exercises

Consider $T_i \in \{0,1\}$ the treatment status of student $i = 1, 2, ..., 1000 - T_i = 1$ if treated $T_i = 0$ if not treated. Potential outcomes $y_i(T_i)$ in students, measured in test results (grades 0 to 100) are defined:

- \blacksquare y0: vector Y(0), assume we can't observe it unless specified.
- \blacksquare y1: vector Y(1), assume we can't observe it unless specified.

- 1.1 What is the value of $y_3(1)$? Describe its meaning—in terms of the potential outcomes framework.
- 1.2 What is the value of $y_5(0)$? Describe its meaning.
- 1.3 Compute Y(1). Describe its meaning.
- 1.4 Suppose T=0. What is the value of y_{20}^{obs} and y_{40}^{miss} ? Briefly explain why. 1.5 Suppose $T_i=1$ for all i=1,2,3,...,1000. What is \bar{Y}^{obs} ?
- 1.6 Imagine you can observe both potential outcomes.
 - (a) What is the causal effect of Project Mentor in student 245?
 - (b) What is the estimated Average Treatment Effect (ATE) of Project Mentor?
 - (c) Does the estimated ATE support the Prime Minister's claims?

In practice, only Y^{obs} will be available after applying the exam. You will observe **one** test score per student, as well as the students' treatment status: either treated or untreated.

After careful consideration, your team assigned N_0 students to control and N_1 students to treatment out of the $N_0 + N_1 \equiv N = 1000$ sampled. The assignment criteria included logistics, the school-year timeline, operation costs and potential political opposition. Treatment was allocated amongsts students per the rule

$$T = W_{school}$$

- 2.1 Explain the assignment rule in simple words
- 2.2 For each of the assignment criteria, provide a brief circumstance that likely motivated Novaria's government to conclude this was the best allocation.
- 2.3 What is the value of N_0 ?
- 2.4 What is the value of N_1 ?
- 2.5 Create a variable for $Y^{obs}(W)$, and name it yobs_w. With this variable:
 - (a) Compute the value of $\bar{Y}^{obs}(1)$.
 - (b) Compute the value of $\bar{Y}^{obs}(0)$.
- 2.6 Write down both expressions $\bar{Y}^{obs}(\cdot)$ more formally, in terms of summations.
- 2.7 Your team knows that $ATE = E(y_i^{obs}|W=1) E(y_i^{obs}|W=0)$ but they don't know why, or how to estimate it from our sample.
 - (a) What is \widehat{ATE} ?
 - (b) Justify your answer in terms of a famous mathematical theorem:

i.
$$\square \xrightarrow{\square} E(y_i|W=1)$$

- iii. Therefore the estimate ...
- (c) Compute $\widehat{A}T\widehat{E}$ using R.
- (d) Reflect on the result. How does it compare to your answers in 1.6b and 1.6c? At this point, do we have any way to diagnose the accuracy of this result?
- 2.8 Again, let's imagine we can observe potential outcomes. In the lecture, it was shown that the ATE can be decomposed in treatment on the treated and selection bias. Write down that expression and estimate the values of:
 - (a) treatment of the treated
 - (b) selection bias

- (c) each individual term in selection bias
- 2.9 What do these values imply for the experiment's design? Is the value for 2.8a a potentially good \widehat{ATE} ? What would be omitted if we were to only consider this value?

Case study 0.7.2

Evaluating AI-assisted learning on student outcomes (continued)

Instructions: Work in pairs or groups of 3; answer the questions as concisely as possible. Type your answers in a single shared document or in the format required by the instructor.

One of you must set up a blank Colab notebook to work on, and share it with the rest. Save any figures or output, and incorporate as required by the instructor.

This is a direct continuation of G.7.3, thus we will work under the context you already have. Continue to use **students** when necessary to answer the questions.

Scenario: You let the Prime Minister know the treatment allocation for the Project Mentor experiment you had previously agreed on is problematic. He hires a team of consultants to help you sort this design problem out, as well as polish other details of the experiment. The following exercises are contain some of the questions asked during the meetings held with the consulting team and the Prime Minister.

Meeting 1

- 1.1 Firstly, you are asked to explain generally why you cannot get a credible average treatment effect from the current treatment allocation. How would outcomes be different we were to scale up the program nationally? (use your "secret" knowledge of the potential outcomes)
- 1.2 You are asked to provide an alternative assignment that would create two groups equally representative of 6th-graders nationally. Create such assignment variable under the name T, and also create $yobs_t$, the outcome we would observe under this assignment. Calculate the \widehat{ATE} . How does this result compare to 2.8a in G.7.3? Without making any further calculations, what do you think the treatment effect among private schoolers will be?
- 1.3 The Prime Minister doesn't believe that your new assignment created comparable groups. One way to provide evidence of balance, is showing the groups have the same composition of public and private schoolers. Formally show there is no evidence to reject the composition is the same. Be as conservative as possible with the variance.

1.4 Imagine everyone can observe potential outcomes. From the definition of ATE, show treatment and control are comparable more decisively.

Meeting 2

While more convinced of your new assignment, the Pime Minister still insists asking for permission to private schools is impractical and will delay matters. Conveniently, the consulting team asks two questions:

- Whether attending a private/public school in Novartia actually creates systematic differences between students; particularly, differences related to the outcome. This has not been formally shown.
- Whether there may be differences in treatment effects between public and private students (e.g. the mean effect is larger for any), as these differences would justify different rollouts.

To provide evidence in favor or against these questions, bear in mind we have to start from the following assumption:

$$y_i(0)|W = 0 \sim Distr(\mu_0, \ \sigma_{0,0}^2)$$
$$y_i(1)|W = 0 \sim Distr(\mu_1, \ \sigma_{1,0}^2)$$
$$y_i(0)|W = 1 \sim Distr(\nu_0, \ \sigma_{0,1}^2)$$
$$y_i(1)|W = 1 \sim Distr(\nu_1, \ \sigma_{1,1}^2)$$

Where $\sigma_{0,0}^2 \neq \sigma_{0,1}^2 \neq \sigma_{1,0}^2 \neq \sigma_{1,1}^2$

- 2.1 In your own words what do these assumptions mean? What do they entail when it comes to testing hypotheses? According to the lecture, what should we assume about the correlation among these random variables if we want to be conservative?
- 2.2 Answer the question about systematic differences in outcomes between public and private schools with the evidence you have.
 - (a) State the appropriate null hypotheses and their alternates.
 - (b) Test them with the appropriate statistic (estimate any parameters you don't know).
 - (c) Tie your conclusions directly to the question with 95% confidence.
- 2.3 Answer the question about differences in treatment effects.
 - (a) State the appropriate null hypotheses (test equality).
 - (b) Make inference on $\hat{\nu}_1, \hat{\nu}_0, \hat{\mu}_1, \hat{\mu}_0$ accordingly.
 - (c) Tie your conclusions directly to the question with 95% confidence.

Meeting 3

Satisfied with your answers, the Prime Minister and consultants approach you with some final questions about the program's broader implications:

- 3.1 **SUTVA violations** In your own words, briefly explain the Stable Unit Treatment Value Assumption (SUTVA). Could implementing Project Mentor violate this assumption in Novaria? Provide a specific scenario illustrating such a violation clearly. How might these externalities affect the accuracy of your estimates?
- 3.2 Alternative policies with proven outcomes (e.g. TaRL) The consultants suggest evaluating cheaper alternatives, like Teaching at the Right Level targeting teaching to each student's current skill level without advanced technology; human mentors, complementary material, smaller traditional groups (more teachers), among others. These alternatives currently have more robust evidence of their effects.
 - (a) What, if any, are some differences between the theory of change underlying TaRL and that of Project Mentor?
 - (b) If differences exist, briefly discuss how you would test them within an experimental design, clearly describing treatments, assignment and measured outcome(s).
 - (c) Apart from the treatment effects, what else is necessary if we wanted to fairly compare any known TaRL intervention to Project Mentor in terms of efficiency?
 - (d) In this comparison, how important do you think scale would be? Briefly describe how costs for one and the other would behave.
- 3.3 Non-compliance Not every school or student may strictly follow the treatment assignment. Describe one realistic scenario of non-compliance in this project. Explain briefly how such non-compliance might bias the estimated treatment effect. Suggest one practical strategy to reduce or mitigate non-compliance.

Week 8 Instructions

Some title

Checklist

Watch the linear models with R: ${\tt lm}\ tutorial^4({\tt Requirement})$
Complete Guided Case Study 4 (Session 1)
☐ Get the bike_rentals dataset here
Complete Guided Case Study 5 (Session 2)
\square Get the student_performance dataset here
Complete Guided Case Study 6 (Session 2)
☐ Get the kc_house_data dataset here
(Optional) Explore Review Notes and further Readings available.

⁴Module 8 > Introduction to the Class lm in the online component of the course.

Guided case study G.8.4

Part A - Bike rentals

Instructions: Work in pairs or groups of three. Solve the exercises for Part A of *Linear Regression* in Colab. Work collaboratively in a single Notebook.

Notebook: Part A

☐ Dataset: bike_rentals.csv

Type your answers in the notebook, and submit your work per the instructor's requirements.

Guided case study G.8.5

Part B - Student performance

Instructions: Work in pairs or groups of three. Solve the exercises for Part B of *Linear Regression* in Colab. Work collaboratively in a single Notebook.

Notebook: Part B

Ш Dataset: student_performance.csv

Type your answers in the notebook, and submit your work per the instructor's requirements.

Guided case study G.8.6

Part C - KC Housing Data

Instructions: Work in pairs or groups of three. Solve the exercises for Part C of *Linear Regression* in Colab. Work collaboratively in a single Notebook.

Notebook: Part C

☐ Dataset: kc_house_data.csv

Type your answers in the notebook, and submit your work per the instructor's requirements.

Additional resources

- Drive: Review Notes

- **E** Drive: Readings

Week 9 Instructions

Some title

Checklist

	Comp	lete (Cod	ling	Lal	b	5	(Session	1))
--	------	--------	-----	------	-----	---	---	----------	----	---

☐ Complete Guided Case 7 (Session 2)

☐ Review the reference material as needed (Optional)

Coding Lab C.9.5

Coding Lab 5— Further regression tools

Instructions: Work individually. Complete all the coding lab's exercises.

Notebook: Further regression tools

Upon completion, submit your work in the format required by the instructor.

Guided Case Study G.9.7

Regression Discontinuity: Replicating *Going to a better school* (Pop-Eleches & Urquiola, 2013)

Instructions: Work in pairs or teams of three. We will go over a section of *Going* to a better school: Effects and Behavioral Responses to examine outcomes differences of children attending higher achievement schools.

Notebook: Guided Case 7— RDD paper replication

Dataset: Schools.dta

► Paper: (Pop-Eleches & Urquiola, 2013)

Scenario: In 2002, the Romanian Ministry of Education centralized the high school admissions system, ranking students by their standardized test scores and matching them to schools in descending order of achievement. This reform generated a compelling natural experiment: some students who barely made it into higher-achieving schools were nearly identical, academically, to those who just missed the cutoff. In this guided case study, you will analyze data from this setting to investigate whether attending a better school causally affects student outcomes. You'll explore the design of the regression discontinuity strategy used by Pop-Eleches and Urquiola (2013), and replicate parts of their analysis using real admissions and outcomes data from Romanian high schools.

A Colab notebook has been set up with the full case directions therein. Submit your coursework in the format required by your instructor.

Additional materials and references

References:

Drive:

- (Pop-Eleches & Urquiola, 2013)
- Causal inference textbook
- Econometrics textbook

Additional materials:

Drive:

- Review notes week 9

Bibliography

Pop-Eleches, C., & Urquiola, M. (2013). Going to a better school: Effects and behavioral responses. American Economic Review, 103(4), 1289-1324. https://doi.org/10.1257/aer.103.4.1289

Week 10 Instructions

Some title